

# Performance evaluation of WMN-GA for different mutation and crossover rates considering number of covered users parameter

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**Abstract.** Node placement problems have been long investigated in the optimization field due to numerous applications in location science and classification. Facility location problems are showing their usefulness to communication networks, and more especially from Wireless Mesh Networks (WMNs) field. Recently, such problems are showing their usefulness to communication networks, where facilities could be servers or routers offering connectivity services to clients. In this paper, we deal with the effect of mutation and crossover operators in GA for node placement problem. We evaluate the performance of the proposed system using different selection operators and different distributions of router nodes considering number of covered users parameter. The simulation results show that for Linear and Exponential ranking methods, the system has a good performance for all rates of crossover and mutation.

## 1. Introduction

With the emergence of several new networking paradigms such as Ad-hoc networks, sensor networks, vehicular networks, cellular networks, optimization modelling and resolution turns out to be crucial to achieve optimized performance networks [1–3]. One such networking paradigm that is requiring the resolution of optimization problems is that of WMNs. At the heart of WMNs are the issues of achieving network connectivity and stability as well as QoS in terms of user coverage. These issues are very closely related to the family of node placement problems in WMNs, such as mesh router nodes placement. Node placement problems have been long investigated in the optimization field due to numerous applications in location science and classification (clustering). In such problems, we are given a number of potential facilities to serve to costumers connected to facilities aiming to find locations such that the cost of serving

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to all customers is minimized. In traditional versions of the problem, facilities could be hospitals, polling centers, fire stations serving to a number of clients and aiming to minimize some distance function in a metric space between clients and such facilities.

WMNs [4,5] infrastructures are currently used in developing and deploying medical, transport and surveillance applications in urban areas, metropolitan, neighboring communities and municipal area networks [6]. WMNs are based on mesh topology, in which every node (representing a server) is connected to one or more nodes, enabling thus the information transmission in more than one path. The path redundancy is a robust feature of this kind of topology. Compared to other topologies, mesh topology needs not a central node, allowing networks based on such topology to be self-healing. These characteristics of networks with mesh topology make them very reliable and robust networks to potential server node failures. In WMNs mesh routers provide network connectivity services to mesh client nodes. The good performance and operability of WMNs largely depends on placement of mesh routers nodes in the geographical deployment area to achieve network connectivity, stability and user coverage. The objective is to find an optimal and robust topology of the mesh router nodes to support connectivity services to clients.

For the mesh router node placement problem, are given a grid area arranged in cells where to distribute a number of mesh router nodes and a number of mesh client nodes of fixed positions (of an arbitrary distribution) in the grid area. The objective is to find a location assignment for the mesh routers to the cells of the grid area that maximizes the network connectivity and client coverage. Network connectivity is measured by the size of the giant component of the resulting WMN graph, while the user coverage is simply the number of mesh client nodes that fall within the radio coverage of at least one mesh router node.

For most formulations, node placement problems are shown to be computationally hard to solve to optimality [7–10], and therefore heuristic and meta-heuristic approaches are useful approaches to solve the problem for practical purposes. Several heuristic approaches are found in the literature for node placement problems in WMNs [11–15].

Genetic Algorithms (GAs) have been recently investigated as effective resolution methods. In this work, we present the results of the effect of mutation and crossover operators in GA for mesh router nodes placement problem. The study aims to identify the mutation and crossover types that work best for instances of different characteristics. A bi-objective optimization, namely, the maximization of the size of the giant component in the network (for measuring network connectivity) and that of user coverage are considered. However in this paper, we use only the number of covered users as a parameter for the system evaluation. In the simulations, we have used different distributions of mesh node clients (Uniform, Normal, Exponential and Weibull).

The rest of the paper is organized as follows. In Section 2 is presented Genetic Algorithm template and its application to mesh router nodes placement. We focus further on mutation types and mutation rate values in Section 3. The crossover operator is described in Section 4. The simulation results are given in Section 5. We end the paper in Section 6 with some conclusions.

## 2. Genetic algorithms

Genetic Algorithms (GAs) [16,17] have shown their usefulness for the resolution of many computationally combinatorial optimization problems. For the purpose of this work, we have used the *template* given in Algorithm 1.

We present next the particularization of GAs for the mesh router nodes placement in WMNs (see [20] for more details).

**Algorithm 1** Genetic Algorithm template

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Generate the initial population  $P^0$  of size  $\mu$ ;
Evaluate  $P^0$ ;
while not termination-condition do
  Select the parental pool  $T^t$  of size  $\lambda$ ;  $T^t := \text{Select}(P^t)$ ;
  Perform crossover procedure on pairs of individuals in  $T^t$  with probability  $p_c$ ;  $P_c^t := \text{Cross}(T^t)$ ;
  Perform mutation procedure on individuals in  $P_c^t$  with probability  $p_m$ ;  $P_m^t := \text{Mutate}(P_c^t)$ ;
  Evaluate  $P_m^t$ ;
  Create a new population  $P^{t+1}$  of size  $\mu$  from individuals in  $P^t$  and/or  $P_m^t$ ;
   $P^{t+1} := \text{Replace}(P^t; P_m^t)$ 
   $t := t + 1$ ;
end while
return Best found individual as solution;

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### 2.1. Encoding

The encoding of individuals (also known as chromosome encoding) is fundamental to the implementation of GAs in order to efficiently transmit the genetic information from parents to offsprings.

In the case of the mesh router nodes placement problem, a solution (individual of the population) contains the information on the current location of routers in the grid area as well as information on links to other mesh router nodes and mesh client nodes. This information is kept in data structures, namely, `pos_routers` for positions of mesh router nodes, `routers_links` for link information among routers and `client_router_link` for link information among routers and clients (matrices of the same size as the grid area are used.) Based on these data structures, the size of the giant component and the number of users covered are computed for the solution.

It should be also noted that routers are assumed to have different radio coverage, therefore any router could be linked to a number of clients and other routers. Obviously, whenever a router is moved to another cell of the grid area, the information on links to both other routers and clients must be computed again and links are re-established.

### 2.2. Selection operators

In the evolutionary computing literature we can find a variety of selection operators, which are in charge of selecting individuals for the pool mate. The operators considered in this work are those based on *Implicit Fitness Re-mapping* technique. It should be noted that selection operators are generic ones and do not depend on the encoding of individuals.

- *Random Selection*: This operator chooses the individuals uniformly at random. The problem is that a simple strategy does not consider even the fitness value of individuals and this may lead to a slow convergence of the algorithm.
- *Best Selection*: This operator selects the individuals in the population having higher fitness value. The main drawback of this operator is that by always choosing the best fitted individuals of the population, the GA converges prematurely.
- *Linear Ranking Selection*: This operator follows the strategy of selecting the individuals in the population with a probability directly proportional to its fitness value. This operator clearly benefits the selection of best endowed individuals, which have larger chances of being selected.
- *Exponential Ranking Selection*: This operator is similar to Linear Ranking but now probabilities of ranked individuals are weighted according to an exponential distribution.

- *Tournament Selection*: This operator selects the individuals based on the result of a tournament among individuals. Usually winning solutions are the ones of better fitness value but individuals of worse fitness value could be chosen as well, contributing thus to avoiding premature convergence. Particular cases of this operator are the *Binary Tournament* and *N-Tournament Selection*, for different values of  $N$ .

### 2.3. Crossover operators

The crossover operators are the most important ingredient of GAs. Indeed, by selecting individuals from the parental generation and interchanging their *genes*, new individuals (descendants) are obtained. It is very important to stress that the crossover operators depend on the chromosome representation. The crossover operator should thus take into account the specifics of mesh router nodes encoding.

### 2.4. Mutation operators

Mutation operator is one of the GA ingredients. Unlike crossover operators, which achieve to transmit genetic information from parents to offsprings, mutation operators usually make some small local perturbation of the individuals, having thus less impact on newly generated individuals.

Crossover is “a must” operator in GA and is usually applied with high probability, while mutation operators when implemented are applied with small probability. The rationale is that a large mutation rate would make the GA search to resemble a random search. Due to this, mutation operator is usually considered as a secondary operator.

## 3. Mutation in genetic algorithms

### 3.1. Mutation operators issues

Many studies in the literature have shown that mutation when effectively combined with selection operators can improve the performance of GAs. Some of the important issues behind the use of mutation operators are as follows:

- *The design of different versions of mutation operators and their evaluation in GA in conjunction with selection operators*: In general, it is difficult to know *a priori* if a simple mutation, such as bit-flip mutation, would produce desired effect. Therefore different types of mutation operators should be designed and evaluated. In fact, their evaluation should be done in conjunction with selection operators.
- *Mutation Rate*: This is among most critical aspects in applying mutation operators. In most applications, mutation rate is kept low and constant through the search. However, the concrete mutation rate has to be tuned. In some works the use of dynamic mutation rates have also been proposed.
- *Effect of Mutation Rate on GA Evolution*: In GAs one critical aspect is keeping diversity of the population and avoid premature convergence to local optima. Certainly, mutation, through small perturbation of the individuals can contribute to maintaining the diversity of the population, if appropriate mutation rates are achieved.

- *Generic vs. Ad Hoc Problem-oriented Mutation Operators*: In general, one could consider the mutation operator as generic, problem-independent operator. This is so because in most cases, small local perturbation to individuals such as bit flip, swap, and so on can be implemented similarly for most combinatorial structures. However, it might be interesting to explore the characteristics of the problem at hand and design some *ad hoc* problem-dependent operators.

### 3.2. Setting mutation rates

Setting the values of parameters in GAs has been and is still a major issue in GA research field. One such parameter is the mutation rate. The complexity of tuning GA parameters, and the mutation rate in particular, comes from the side-effect of one operator on the rest of operators. Ideally, tuning should be able to explore the synergies among different operators.

#### 3.2.1. Population size, crossover and mutation rate

Among the different GA parameters, population size, crossover rate and mutation rate have considerable effect on GA convergence and, consequently, the quality of solution found. Some research studies reported in the literature suggest that there are direct relations among selection strategies, crossover rate and mutation rate. Regarding population size vs. mutation rate, the issue here is whether it would be more beneficial for the genetic search to use: (a) a small population size and rather large mutation rate, or (b) large population sizes and low mutation rate. The choice could have a significant impact on the GA convergence.

#### 3.2.2. Mutation rate

As can be seen from above, setting the mutation value is difficult, in part due to the many other GA parameters to be set and the existing synergies among them. In the literature we would find essentially two ways to set the mutation rate: (a) using constant values and (b) using variable mutation rate. In the former, considered as the easiest way, the mutation rate is kept unchanged during the whole genetic search process. In this case, the value of the mutation rate can be fixed either *a priori* (based on an experimental study) or computed based on some problem size parameter. For instance, some authors have explored the advantages and limitations of using the  $1/L$  heuristic, in which the mutation rate is set to  $1/L$ , where  $L$  stands for the chromosome string length [18].

In the second group, mutation rate is changed during the genetic search process. The difficulty here is how to find an appropriate decreasing function of mutation rate. One such possible function is linear function, that is, mutation rate linearly decreases along the search process. One implementation would then be to keep mutation rate constant during a certain number of generations and then decrease it linearly. Some more advanced schemes proposed in the literature suggest using self-adaptive mutation rates either by splitting the population into sub-populations and using specific mutation rates to sub-populations or by using a ranking of the individuals in the population and then assign to individuals mutation according to the rank [19].

### 3.3. Mutation operators for mesh routers nodes placement in WMNs

In the case of mesh routers node placement, the matrix representation is chosen for the individuals of the population, in order to keep the information on mesh router nodes positions, mesh client positions, links among routers and links among routers and clients. The definition of the mutation operators is therefore specific to matrix-based encoding of the individuals of the population. Several specific mutation operators were considered in this study, which are move-based and swap-based operators.

	0	1	2	3	4	5	6	7	8	9	10	11
0	C											C
1												
2									C			
3					C		C					
4		C					R					
5				C	R			C'				
6												
7												
8				C	R					C		
9				C								
10								C				
11				C'		R		C				

Fig. 1. Single mutate operator.

### 3.3.1. SingleMutate

This is a move-based operator. It selects a mesh router node in the grid area and moves it to another cell of the grid area (see Fig. 1).

### 3.3.2. RectangleMutate

This is a swap-based operator. In this version, the operator selects two “small” rectangles at random in the grid area, and swaps the mesh routers nodes in them (see Fig. 2).

### 3.3.3. SmallMutate

This is a move-based operator. In this case, the operator chooses randomly a router and moves it a small (*a priori* fixed) number of cells in one of the four directions: up, down, left or right in the grid (see Fig. 3). This operator could be used a number of times to achieve the effect of SingleMutate operator.

### 3.3.4. SmallRectangleMutate

This is a move-based operator. The operator selects first at random a rectangle and then all routers inside the rectangle are moved with a small (*a priori* fixed) numbers of cells in one of the four directions: up, down, left or right in the grid (see Fig. 4).

### 3.3.5. Time efficiency of mutation and selection operators

Simple mutation operators, such as bit-flip or simple move are very efficient as only small changes are done in the combinatorial structure. However, mutation based on making larger perturbations of the individual could be time costly given they are applied a total expected number of  $p_m \cdot population\_size$ ,

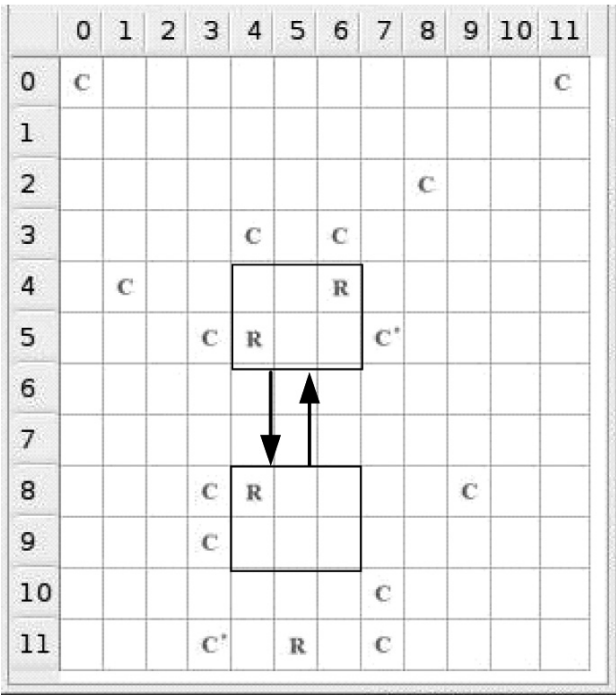


Fig. 2. Rectangle mutate operator.

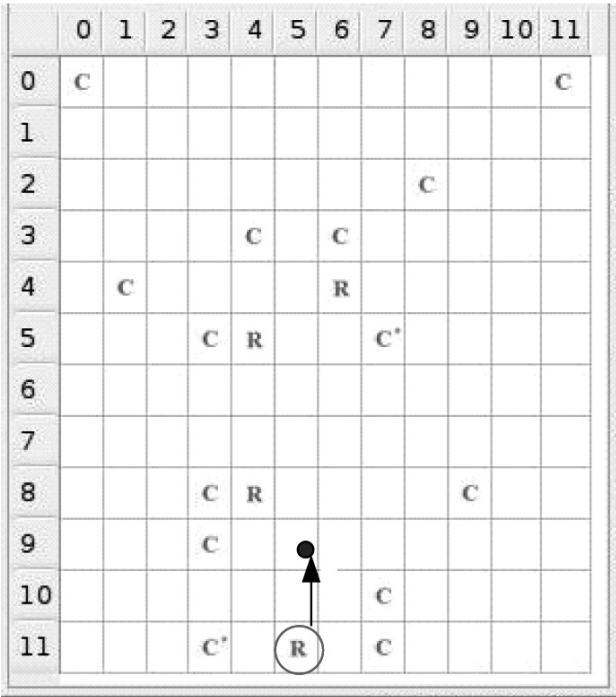


Fig. 3. Small mutate operator.

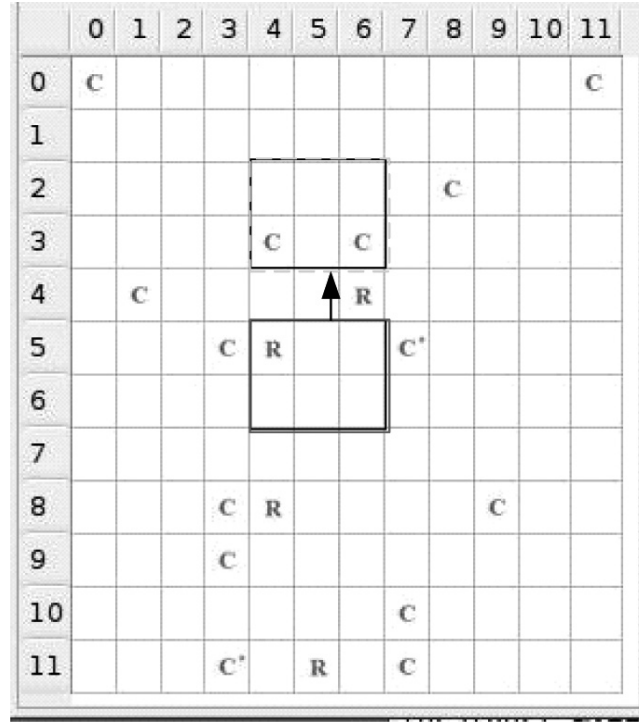


Fig. 4. Small rectangle mutate operator.

where  $p_m$  denotes the mutation probability. This amount is to be multiplied by the time cost of performing one mutation, which in case of rectangle mutate and small rectangle mutate are  $O(grid\_side \times grid\_side)$ . The computational effort is even larger for the crossover operators as in this case the grid area has to be explored to find the sparsest and densest areas.

### 3.4. Crossover operators

The crossover operator selects individuals from the parental generation and interchanging their *genes*, thus new individuals (descendants) are obtained. The aim is to obtain descendants of better quality that will feed the next generation and enable the search to explore new regions of solution space not explored yet.

There exist many types of crossover operators explored in the evolutionary computing literature. It is very important to stress that crossover operators depend on the chromosome representation. This observation is especially important for the mesh router nodes problem, since in our case, instead of having strings we have a grid of nodes located in a certain positions. The crossover operator should thus take into account the specifics of mesh router nodes encoding. We have considered the following crossover operator, called *intersection operator* (denoted `CrossRegion`, hereafter), which take in input two individuals and produce in output two new individuals (see Algorithm 2).

## 4. Proposed and implemented WMN-GA system

In this section, we present WMN-GA system. Our system can generate instances of the problem using different distributions of client and mesh routers.



**Algorithm 2** Crossover Operator

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1:**Input:** Two parent individuals  $P_1$  and  $P_2$ ; values  $H_g$  and  $W_g$  for height and width of a small grid area;  
2:**Output:** Two offsprings  $O_1$  and  $O_2$ ;  
3:Select at random a  $H_g \times W_g$  rectangle  $RP_1$  in parent  $P_1$ . Let  $RP_2$  be the same rectangle in parent  $P_2$ ;  
4:Select at random a  $H_g \times W_g$  rectangle  $RO_1$  in offspring  $O_1$ . Let  $RO_2$  be the same rectangle in offspring  $O_2$ ;  
5:Interchange the mesh router nodes: Move the mesh router nodes of  $RP_1$  to  $RO_2$  and those of  $RP_2$  to  $RO_1$ ;  
6:Re-establish mesh nodes network connections in  $O_1$  and  $O_2$  (links between mesh router nodes and links between client mesh nodes and mesh router nodes are computed again);  
7:**return**  $O_1$  and  $O_2$ ;

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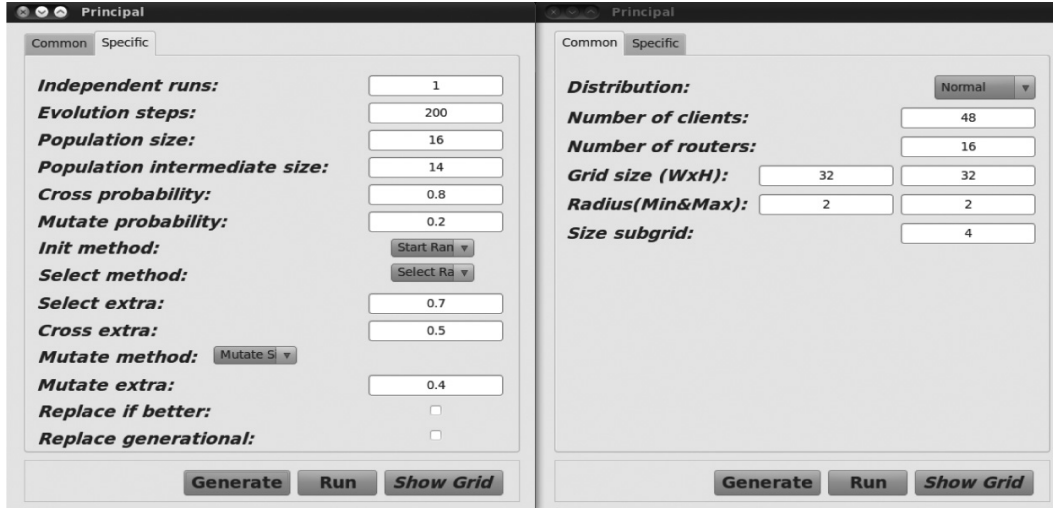


Fig. 5. GUI tool for WMN-GA system.

The GUI interface of WMN-GA is shown in Fig. 5. The left side of the interface shows the GA parameters configuration and on the right side are shown the network configuration parameters.

For the network configuration, we use: distribution, number of clients, number of mesh routers, grid size, radius of transmission distance and the size of subgrid.

For the GA parameter configuration, we use: number of independent runs, GA evaluation steps, population size, population intermediate size, crossover probability, mutation probability, initial methods, select method.

## 5. Simulation results

We carried out many simulations to evaluate the performance of WMNs using WMN-GA system.

In this work, we considered the number of covered users parameter. The number of Mesh Routers is considered 16. We take in consideration four distribution methods: Exponential, Normal, Uniform and Weibull. Six selection operators are used: Best, Exponential Ranking, Linear Ranking, Binary Tournament, N Tournament and Random.

In Figs 6, 7, 8 and 9 are used box plots to analyse the range of data values. Each box plot shows the median of each simulation data (the median is noted by the notch), the upper quartile (25 th and 75 th percentile, respectively) and the outliers. The whiskers represent the lowest data which is still within

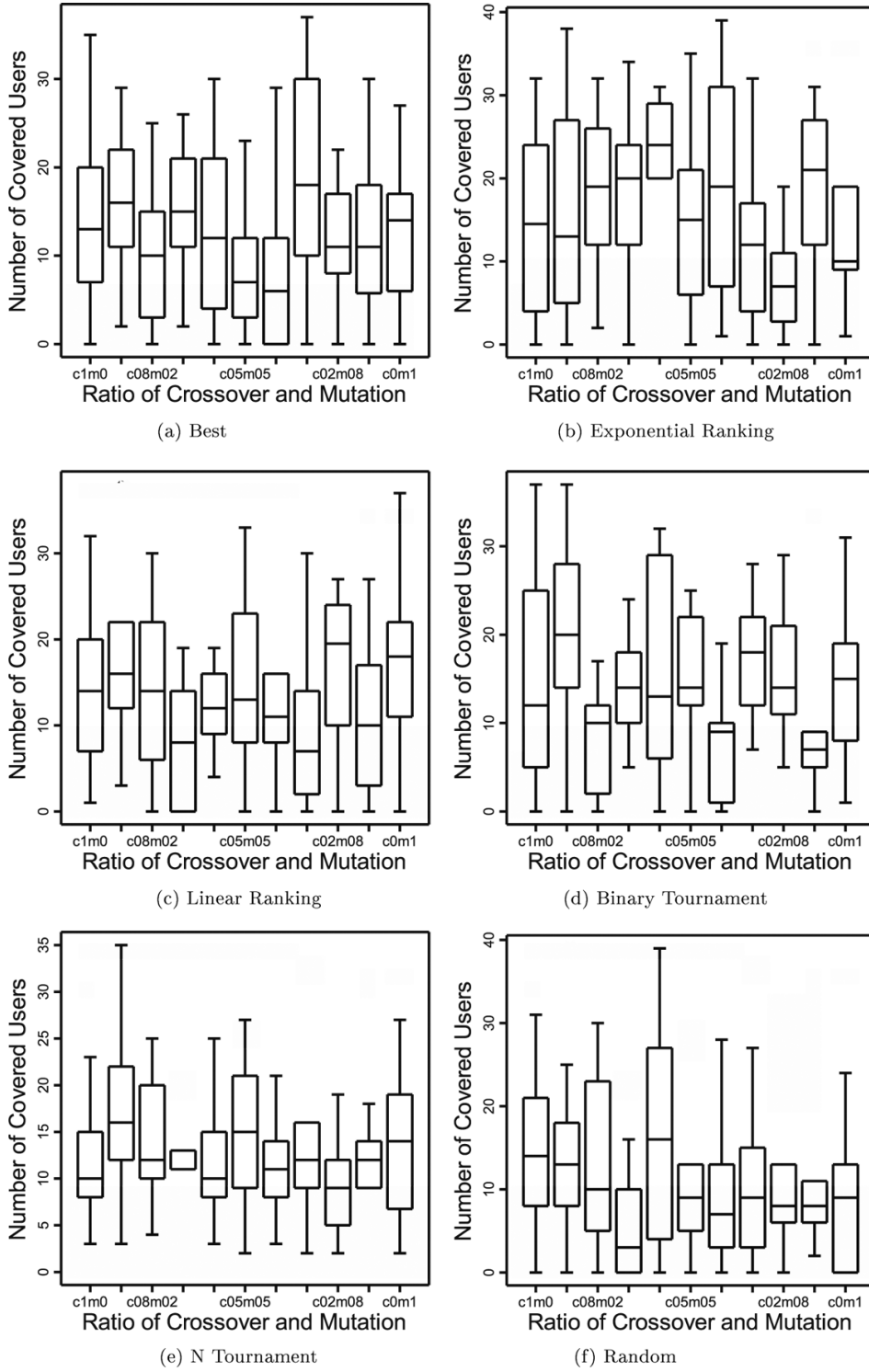


Fig. 6. Number of covered users vs. ratio of crossover and mutation for exponential distribution.

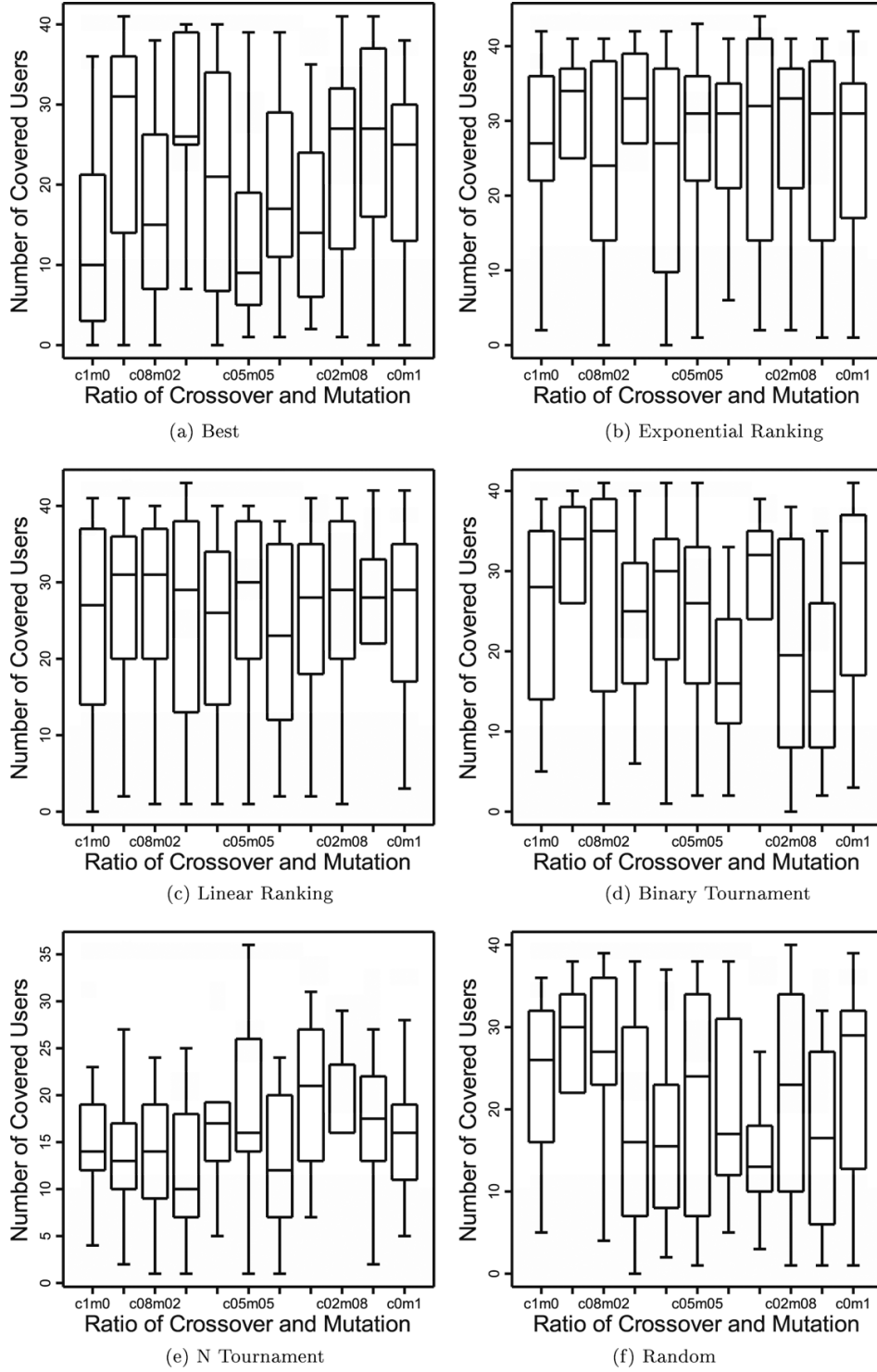


Fig. 7. Number of covered users vs. ratio of crossover and mutation for normal distribution.

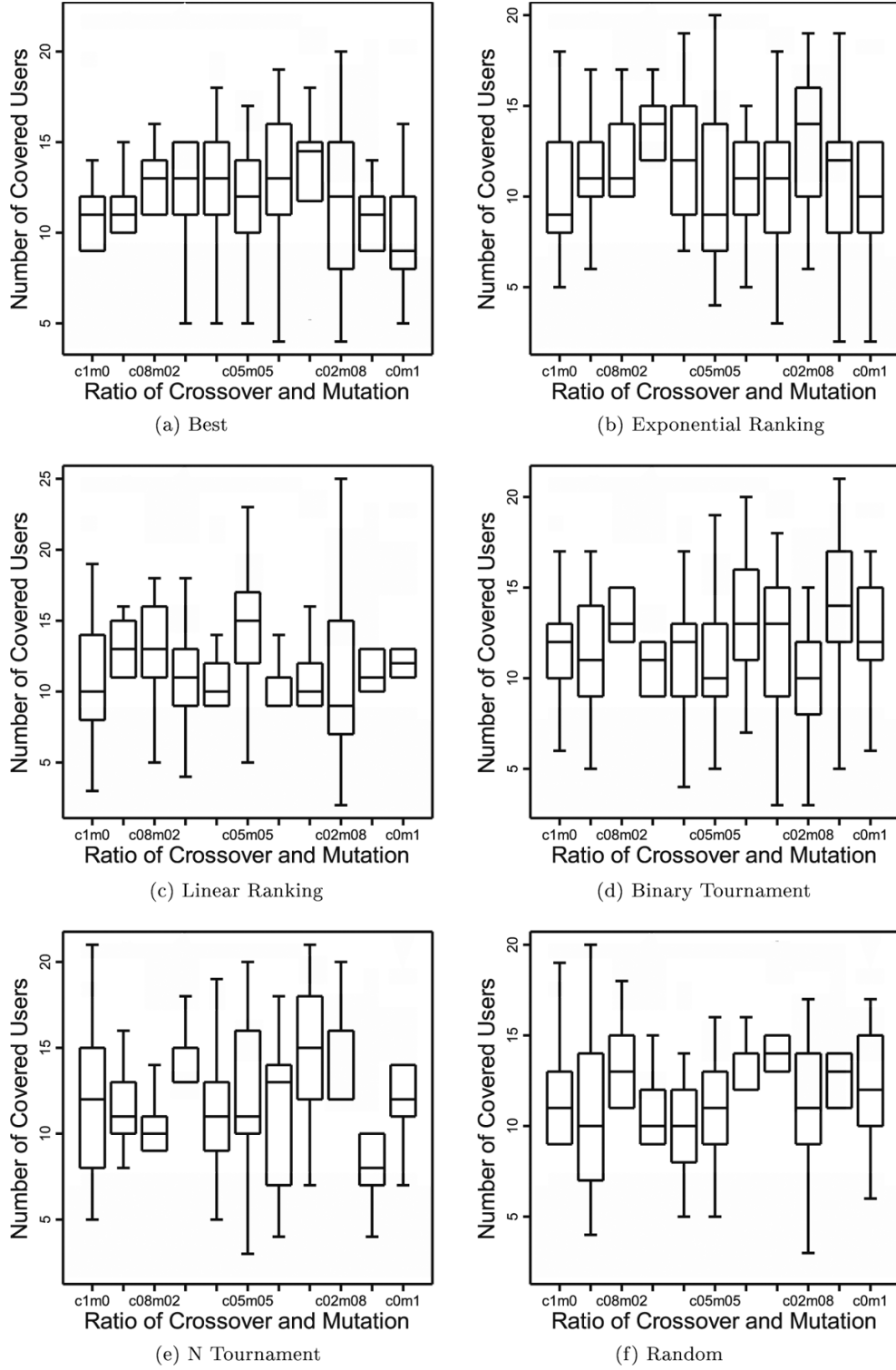


Fig. 8. Number of covered users vs. ratio of crossover and mutation for uniform distribution.

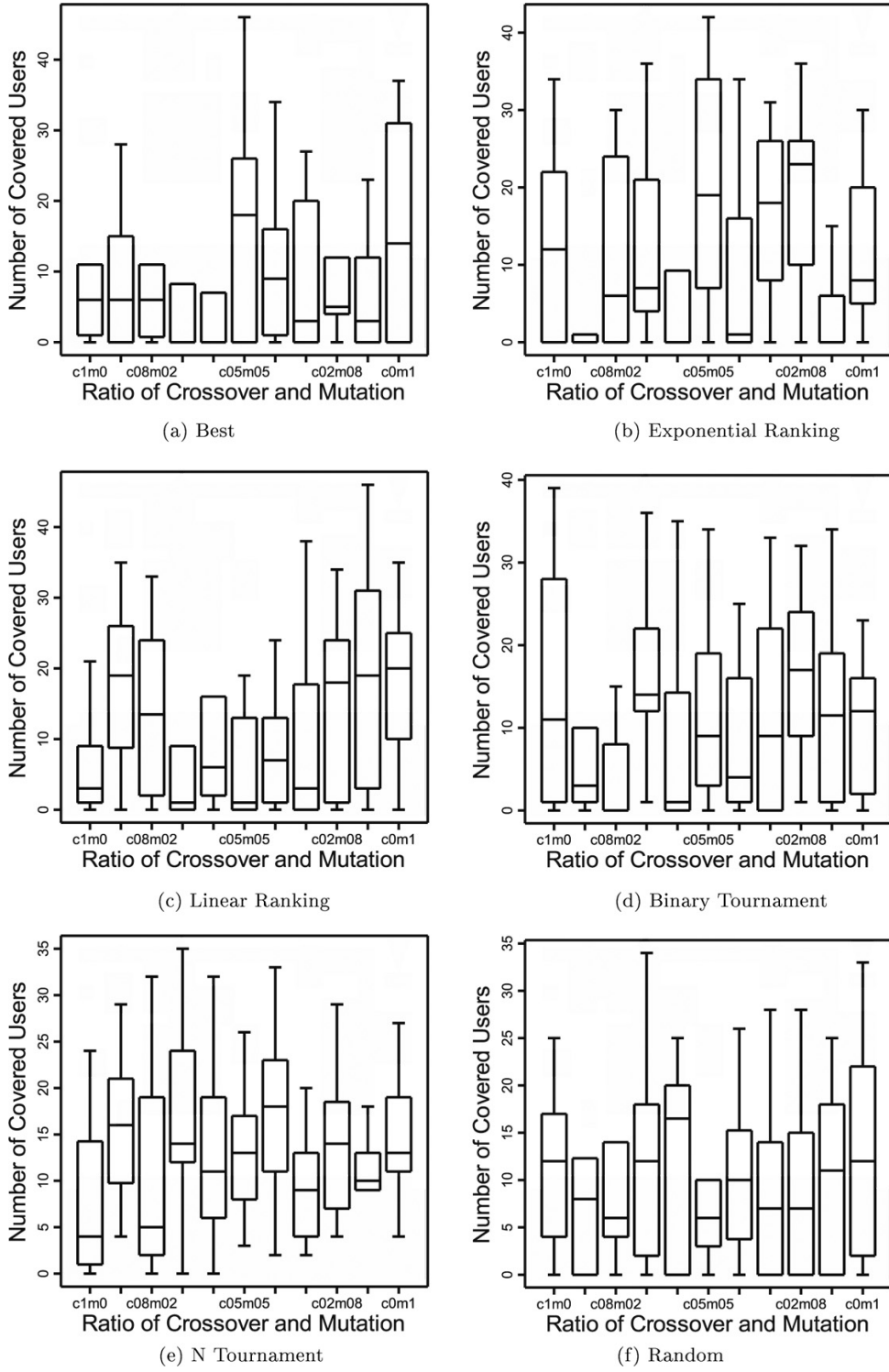


Fig. 9. Number of covered users vs. ratio of crossover and mutation for weibull distribution.

1.5 inter-quartile range of the lowest quartile and the highest data which is still within 1.5 inter-quartile range of the upper quartile.

In Fig. 6 is shown the number of covered users vs. ratio of crossover and mutation for exponential distribution. The maximal number of covered users among these selection operators is achieved by Exponential Ranking operator. The maximum number of covered users is 25. From the results, we can see that Exponential Ranking has better performance. Also, Linear Ranking and Binary Tournament have better behaviour than Best, N Tournament and Random selection operators.

In Fig. 7 is shown the number of covered users vs. the ratio of crossover and mutation for normal distribution. From the results, we can see that Exponential Ranking and Linear Ranking operators have almost the same performance, the number of covered users is almost stable for different rates of crossover and mutation, but for  $c = 90\%$  and  $m = 10\%$  the Exponential Ranking has a bigger number of covered users (35 users). Best operator reaches the best coverage for  $c = 90\%$  and  $m = 10\%$  but for the other rates it covers only few users. For the Binary Tournament the maximal number of covered users is the same with Exponential Ranking but in Exponential Ranking the number of covered users is more stable for all rates of crossover and mutation. N Tournament operator has a bad coverage, the number of covered users is very small. For Random operator the number of covered users is bigger for  $c = 90\%$  and  $m = 10\%$  but for other rates it covers only a small number of users.

In Fig. 8 is shown the number of covered users vs. the ratio of crossover and mutation for uniform distribution. As can be seen, the performance for all these selection operators is almost the same and it is not good because the number of the covered users is less than 15 users.

In Fig. 9 is shown the number of covered users vs. the ratio of crossover and mutation for weibull distribution. The maximum number of covered users is 23 users and is achieved when  $c = 20\%$  and  $m = 80\%$ . Other operators offer a small number of covered users.

From all simulation results, we can see that for normal distribution, different rates of crossover and mutation, and different selection operators, the best performance is for Exponential Ranking.

## 6. Conclusions

In this work, we have proposed and implemented a system based on GAs to solve the connectivity problem in WMNs. We call this system WMN-GA.

We evaluated the performance of the proposed system using different genetic operators and different distributions of router nodes considering number of covered users parameter.

The simulation results show that for Exponential and Linear Ranking methods, the system has a good performance.

In the future work, we would like to compare the performance of WMN-GA system with other optimization algorithms.

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